Optimal Allocation of Distributed Generation in Distributed Network with Genetic Algorithm

ENG470 Engineering Honours Thesis

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Declaration

I declare this thesis is my own account of my research under the guidance of my supervisor, Gregory Grebbin, and contains as its main content work which has not previously been submitted for a degree at any tertiary education institution. Information derived from the published and unpublished work of others have been acknowledged in the text and a list of references is given in the bibliography.

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Abstract

With the higher and higher demand by people for the quality and reliability of the power supply, the centralized power grid cannot meet the requirements. Distributed generation access to the distributed network is an inevitable trend of the development of power industry. It is also one of the important aspects of the development of a smart grid. Distributed Generation is a small scale, low investment and clean power resource. Installing distributed generation in the network can also have positive effects of the networks, such as lower losses, stable voltage and so on; these effects are related to the location and sizing of distributed generation. So this thesis is about optimal location and sizing of distributed generation in distributed network.

At first, I introduce the definition of distributed generation and some common types of DG, such as wind power and PV power. Using Powerfactory simulate IEEE 14 system was simulated to find the how the DG affects the power losses and voltage quality of the network.

According to the analysis above, a model was built with the lowest investment and power losses and the highest voltage quality based on IEEE 14 buses system. The model was simulated in PowerFactory; calculated the power flow using Powerfactory and used adaptive genetic algorithm to solve the optimal problem. The results of the case study will prove that installing distributed generation can decrease the power losses and improve the voltage quality.

Finally, from the practical applications aspect, some directions for future research in this problem have been indicated.

Keywords: Distributed Networks, Distributed Generation, Optimal Allocation, Adaptive Genetic Algorithm.

Content

Chapter 1. Background

1.1 The reasons for finding the optimal placement of distributed generation in the network

The purpose of optimizing the allocation of distributed generation in a distributed network is to make distributed network more effective.

The development of the communities increases the requirement of energy, and electric power is an indispensable form of energy. So, with the decrease of non-renewable energy sources, the structure of electrical grid needs to change. Air pollution, safety issues, financial issues and the electrical market are challenges that will impact the development of electrical generation as well. The pollution problem has motivated scientists and engineers to research and develop forms of renewable energy [1]. Therefore, the development of renewable energy such as wind and solar energy is a concern to countries, the power sector, researchers, universities and individuals.

There are some comparisons between distributed and centralized generation [2]. The disadvantages of centralised generation:

(1) **Safety and stability issues.** The big system, complex grid, and it is difficult to timely control may cause the butterfly effect. For example, a Germany power station cut two transmission lines to let a ship cross a river leading to a huge blackout in the year 2006 [3].

(2) **Environment problem.** Centralized generations are mainly thermoelectricity power generations. These generators not only use non-renewable resources, but also pollute the environment.

(3) **The financial cost of building.** There are a lot of sparsely populated and remote areas in the world. The grids are difficult to cover those areas. It may cause increase in cost.

The advantages of distributed generation:

(1) Some distributed generations are clean and green. Distributed generation can use clean energy as the fuel. It also includes power generation by wind, solar, natural gas and tidal, thus reducing the emissions of Carbides and Sulfide, obviously reducing the pollution.

(2) Efficient use of energy. The connection of distributed generation can change the

power flow of the grid. Decent allocation and capacity of the generators can reduce the losses and improve the node voltages. It can make almost full use of energy, with high efficiency. This point will be verified in this report.

(3) Safety performance improved. The connection of distributed generation can increase the reliability of the grid. The generation can still supply power to important loads when there is vandalism or accidental disaster [4].

(4) Distributed generation can reduce the construction of big power grids, so reducing the losses of transmission. Supply electricity close to the consumers can reduce the high losses caused by long distance transmission.

(5) Accelerate the improvement of the electricity market development. If the permeability of distributed generation increases, the power supply will be diverse. The electricity bills will be effectively controlled.

For the reasons above, we need to fully use the benefits of distributed generation (DG), and let it be positive and try to avoid the negative effects. The performance of DG is closely related to the allocation of generators. The function of DG is not only supply power to the network, but also can aid the whole grid by reducing demand during peak times and by minimizing congestion of power in the network [5]. When there is a malfunction in the system, DG can be used in islanded mode and produce power to the necessary loads until the system is fixed. DG can also reduce the losses of transmission, increase the quality of voltage and decrease the cost of long distance transmission. However, if we cannot find a decent placement and sizing of DG, the losses will be very high instead, and cause the node voltage drops and change the power flow. This shows that different placement of DG can affect the entire system, therefore, optimizing the placement of DG is highly important.

1.2 Research on optimal placement of distributed generation

Optimal allocation of distributed generation in distributed networks means finding out the optimal location and capacity of distributed generation. The location and capacity of the installed distributed generation can affect the performance of distributed network directly. Allocating distributed generation to distributed networks is a big challenge to the electricity researchers [6]. If many distributed generators access the network, the researchers cannot accurately predict how the power flow changes, which will affect the plan of distributed generation. Bad allocation of distributed generation will have negative effects of voltage drops and power losses. So a good distributed generation allocation plan can increase the reliability of a network.

The optimal allocation of distributed generation is a multi-objective and multi-constraints optimization problem. The objectives may have constraints to each other, so, in order to find the optimal way, researchers should predict the installed distributed generation effects, thus finding out the optimal location and capacity of the distributed generation to make the network more reliable.

There are a lot of on going research around the word to solve this problem. Literature [6], states a method for siting and sizing of distributed generation in the distributed network expansion planning with genetic algorithm by taking into account the influence of distributed generation on power flow. Literature [7], uses losses cost, investment cost, fuel cost as the objectives to build an optimal system by Diff Algorithm. Literature [8], optimized the voltage profiles by Evolutionary Algorithms to find out the optimal capacity of distributed generation. Literature [9], used voltage stability as the optimal system; used Lagrange multipliers to analyze the optimal allocation of distributed generation. Literature [10], built a system with optimal losses and operating cost by an improved Particle Swarm Optimization algorithm. Literature [11], used Tabu Search Algorithm to find out an optimal system with lowest losses. Literature [12], used the objective in having the highest output active power of distributed generation by using Linear Programming algorithms. Literature [13], analyzed the effect of losses after distributed generation access to the network, use the lowest loss as the objective by an improved simulated annealing algorithm. The authors then compared the results between this algorithm and genetic algorithm to prove that his algorithm has better convergence rate. Literature [14], used the objectives as the lowest investment cost and active power losses cost by using genetic algorithm. Then compared the result between Genetic Algorithm and Nonlinear Optimization Algorithm to prove that the Genetic Algorithm has more applicability to this problem. Literature [15], researched the effect of voltage caused by distributed generation and optimal allocation of distributed generation with Particle Swarm Optimization. Literature [18], proposed an improved genetic algorithm which is based on a new matrix-code which combined the integer code of distributed generation with 0-1 code of the distributed network to iterate parallel needs, saving the time on decoding.

Chapter 2. Definition of Distributed Generation and its effects on Distributed Network

2.1 introduction

Nowadays, the power grid is turning from a single traditional centralised generation to distributed and centralised combined generation [16]. So it is important to know about the distributed generation characteristic and classifications to find out the optimal distributed generation to be installed. It can help to improve the power quality and let the distributed generation be more economical and reliable [17].

2.2 Definition of Distributed Generation

Distributed generation technology was there for a long time, such as the small thermal power station. However, due to the technology not being refined, it lead to a lot of polluted air. Most of these simple distributed generation have been replaced by renewable energy generation. Distributed generation was proposed and spread by American Public Utility Regulatory Policies Act (PURPA) in the year 1978. The U.K. calls it Embedded Generation, North American countries call it Dispersed Generation, and some countries call it Decentralised Generation. Most of people call it distributed generation, DG for short [18].

DG was defined as a small capacity power generation system connected to a distributed network and be allocated in the load side originally. The wind generation and solar generation are independent generation systems connected to the distributed network from the transmission network. Nowadays, many big wind farms are directly connect to the transmission network. In other words, DG is the generation plant which is connected to the distributed network dispersedly, include wind farms, PV power stations, small hydropower plants, and small thermal power stations and so on. Some people think DG is the small capacity power generation system which can meet customers' demands, use the local natural energy, and also can adapt to the regional environment and natural conditions [19]. DG can not only improve the efficiency of using energy, but also some clean energy DG can reduce the damage to the environment; it is the best choice of the new clean energy.

2.3 Classification of Distributed Generation

The primary energy can be classified by renewable energy and non-renewable energy. The renewable energy generations include wind, solar, tide, small hydropower plant and so on. The non-renewable energy generations include internal combustion engine, fuel cell, and cogeneration and so on [20]. According to the size, DG can be classified by micro (less than 2kW), mini (2-10kW, single phase or 30kW three phase), small (greater than 10kW single phase or 30kW three phase, no more than 1MW), medium (1MW to 5MW) and large (greater than 5MW) [21].

2.3.1 Wind Generation

Wind generation is a clean, no pollution renewable energy. Wind turbine converts the wind kinetic energy into electrical power. Wind generation does not need fuel so it is clean. The power depends on the wind speed. The principle: The wind let blades turn and covert wind energy into low speed rotational energy, then produce power through the gear box, brake which are connected to the generator. Wind generation is the most mature, popular and have good development future. With the development of wind generation, the reliance of fossil fuels may be reduced.

2.3.2 Solar Power Generation

Solar power generation is converting sunlight into electricity. The significant component is Photovoltaic, PV. For solar power, the produced power is changed with different sunlight's intensity. In addition, the performance of PV cell is related to its surface temperature. High temperature may cause the output power decrease [22].

The advantages of solar power are: no fuel consumption, no pollution, no geographical restrictions, easy to maintain, safe and reliable. However, the output power is effected by the weather conditions and high investment cost of solar system are the disadvantages.

2.3.3 Fuel cells

A fuel cell is a generating device that convert the chemical energy into electricity from a fuel through the chemical reaction of hydrogen ions with oxygen. Classified by electrolyte, fuel cells include Proton exchange membrane fuel cells (PEMFCs), Phosphoric acid fuel cell (PAFC), Molten carbonate fuel cells (MCFCs), Solid oxide fuel cells (SOFCs), Alkaline fuel cell (AFC), Direct methanol fuel cell (DMFC) and so on [23]. The advantages are: 1. High energy converting efficiency, up to 95%. 2. High power generation efficiency, up to 70%. 3. Clean, no pollution. 4. So many types mean so many kind of fuels, so the fuels are flexible and easy to find. 5. Safety. 6. Easy to install and maintain.

2.3.4 Cogeneration

Traditional fuel generation releases a lot of heat to the air. Cogeneration or combined heat and power (CHP) is using heat engine or power station to generate electricity and heat at the same time. Generation of electricity and useful heating and cooling from the combustion of a fuel at the same time is called combined cooling, heat and power (CCHP) [24].

In addition to these four popular types of distributed generation, other types include hydro power, biomass, geothermal power and so on.

2.4 Impacts of distributed generation on distribution network

With more and more distributed generation access to distributed network, it leads to some challenges to the network planning researchers. In order to optimally allocate distributed generation, we have to consider about the impacts of distributed generation on distribution networks [25].

a. The distributed generation can affect the power losses of a network, if the location and size of distributed generation are not decent, it may cause the power losses to increase, and that can lead to voltages to be too high or low on some nodes. In addition, in some types of distributed generation, such as wind power or solar power are instable or intermittent [26]. So distributed generation may also lead to some uncertainty factors of operators.

b. Generally, planning to build a distributed network need about 5 to 10 years [25]. During this time, the demand of network may increase. Planning a distributed network is a dynamic problem, so installing distributed generation at the same time will be more difficult to optimise the network.

c. When the distributed generation access to distributed network, if the installed area need more power, distributed generation can supply electricity to reduce the investment cost of network. However, if the electricity supply of the area is already sufficient, the distributed generation will not be fully used. This situation may waste the cost and energy.

d. Installing distributed generation can improve the power quality of the network. Decent allocation of distributed generation can improve the voltage profile, which means letting the voltages be closer to the rated voltage to increase the efficiency. When the load is high, installing distributed generation can supply power to the loads that makes the network more stable. However, the contribution of some distributed generation depends on the weather or environment. The sudden starts and stops of distributed generation may cause voltage fluctuations, flicker or droop [27]

e. Distributed generation can increase or decrease the reliability. Distributed generation can supply power to the near loads to increase the reliability. If there is a system fault, distributed generation can convert to islanded operation to supply power [28].

In conclusion, there are a lot of impacts about the economy and reliability. The effects of power losses and voltage profiles of distributed generation are analyzed below.

2.4.1 The effect of DG on voltage profiles

Most distributed networks are closed-loop designs and open loop operation, so that the nets are radial. With the DG access to the networks, power flow will be changed to bidirectional, leading to the change.

If the output power of DG can be adjusted following the load, we can control the voltage fluctuations [29]. When the DG is intermittent or unstable, such as wind generation or solar generation, it is difficult to control the output power. This may also lead to affect the voltage fluctuation. If the DG allocation is unreasonable this may make the power flow disorder, leading to affect the voltage fluctuation. If we optimise the placement and sizing of DG, this can improve the voltage quality of the entire network, increasing the reliability.

For example, figure 2-1 shows one of the feeder lines of a distributed network. Assume there are n loads on each bus on this feeder line. The impedance of each branch is

$Z_i = R_i + jX_i$. The power of loads and distributed generation are $P_i + jQ_i$ $and\ P_{DGj} + jQ_{DGj}$

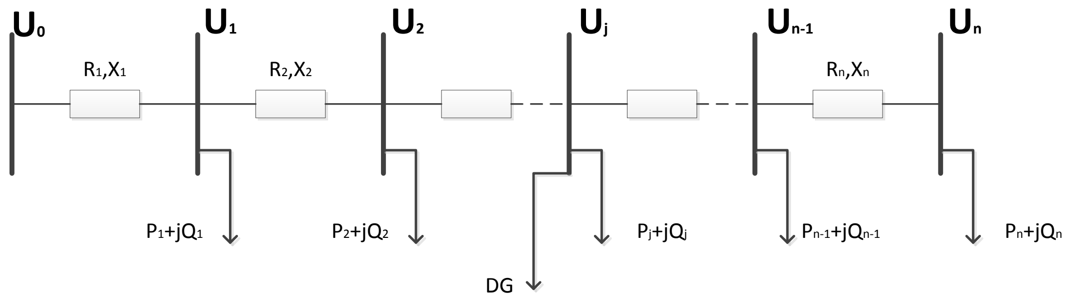

Figure 2-1 Example for one of feeder line

a. Without distributed generation

The current on branch k:

$$I_k = \sum_{i=k}^{n} I_{Li}\, , \mathrm{k} = 1, 2, \dots, \mathrm{n}$$

(2-1)

Where, I_{Li} is the load current, on ….i.

The current will produce a voltage drop, given by

$$\Delta U_k = I_k Z_k, k = 1,2, \dots., n$$

(2-2)

The voltage on each bus:

$$U_k = U_0 - \sum_{l=1}^{k} \Delta U_l\, , k = 1,2, \dots, n$$

(2-3)

b. With distributed generation built in

If a distributed generation is built on bus j, the current on each branch:

$$I'_k = \begin{cases} \sum_{i=k}^{n} I_{Li} - I_{DGj}, k \le j \\ I_k, k > j \end{cases}$$

(2-4)

Where, I_{DGj} is the input current of distributed generation on bus j.

The voltage drop on each branch:

$$\Delta U_k' = I_k' Z_k = \begin{cases} Z_k(\sum_{i=k}^{n} I_{Li} - I_{DGj}), k \le j \\ Z_k I_k, k > j \end{cases}$$

(2-5)

The voltage on each bus:

$$U_k' = U_0 - \sum_{l=1}^{k} \Delta U_l', k = 1,2, \dots, n$$

(2-6)

Compare the equation (2-2) and (2-5), the voltage drop on bus j reduce $Z_k I_{dgj}$, the losses on the branches after bus j has no change. The voltage on bus j increase, leading to the buses after j to increase as well, improving the voltage quality.

When the capacity of distributed generation increase, I_{DGj} will increase, from equation (2-4) and (2-5), the current and voltage drop on the branches before (on the left side) bus j are all decreased, so that the voltages on the buses before bus j are increased and more closed to the rated voltage, that means the voltages have been improved. However, if the capacity of distributed generation is too high, when the $I_{DGj} > I_j$, the power flow will change the direction. There will be a bus of demarcation P. The power flow is shown in figure 2-2 below, the arrow shows the direction of power flow. The voltages on the buses from 0 to P will decrease, and the voltages from bus P to j will get higher. When the voltage difference value between U_0 and U_P become higher than the voltage difference value between U_P and U_j, the voltage on the distributed generation installed bus U_j will be higher than the system voltage U_0. To make sure the network operates safely, it is necessary to limit the capacity of installed distributed generation as soon as we improve the bus voltage to prevent the bus voltage getting too high.

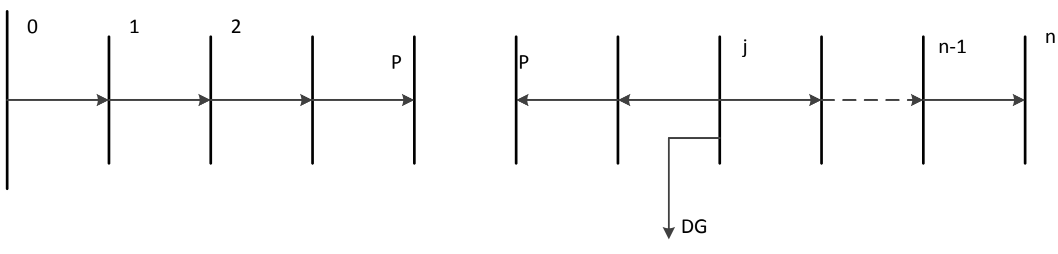

Figure 2-2 Power flow direction in the feeder line

From equation (2-5), if the distributed generation current $I_{DGj} \leq I_j$, changes location of distributed generation to bus 0, the number of buses with voltage drops is decreased will be fewer, which means the distributed generation can affect the network less; Otherwise, if the distributed generation moves to the end of line, bus n, the number of buses which voltage drop is decreased will be more, the distributed generation can affect the network more.

In conclusion, to ignore the voltage becoming higher than the limit due to power backflow, it is important to install optimal capacity of distributed generation. The capacity constraints of distributed generation could be changed depend on the location.

2.4.2 The effects of accessed DG on power losses

Most of distributed networks are radial. With the DG access to the networks, power flow will be changed to bidirectional, leading to changes in the losses.

Figure 2-3 below is a simple mode with DG connected, assume the voltage is same on every bus and the load power can meet the demand. L1 is the distance between DG and substation.

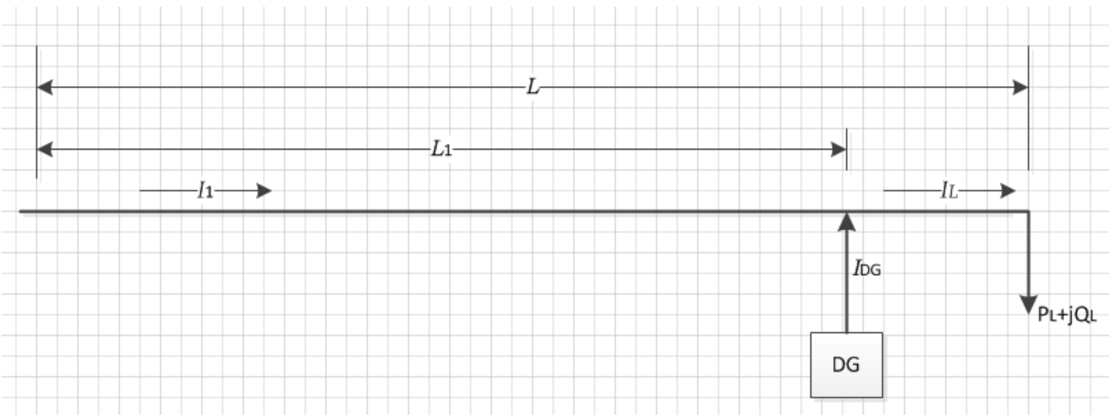

Figure 2-3 simple mode with DG

Without distributed generation, the power losses

$$P_{Loss} = \frac{(P_L^2 + Q_L^2) rL}{V^2}$$

(2-7)

Where, P_L, Q_L are active power and reactive power of the load respectively. r is impedance per unit length of the line, L is the length of the line. V is the voltage on the laod.

With distributed generation,

$$P_{loss-DG} = \frac{(P_L^2 + Q_L^2)r(L - L_1)}{V^2} + \frac{(P_L - P_{DG})^2 + (Q_L - Q_{DG})^2}{V^2} rL_1$$

(2-8)

The difference between with and without distributed generation,

$$\Delta \mathrm{P} = P_{Loss-DG} - P_{loss} = \frac{P_{DG}(P_{DG} - 2P_L) + Q_{DG}(Q_L - 2Q_{DG})}{V^2} rL_1$$

(2-9)

From equation (2-9), we can see that installing distributed generation can influence the losses in networks and the losses are related to the capacity and the location of distributed generation.

2.4.3 Case study

Simulate IEEE 33 buses system to find the relationship between the allocation of generation and the voltage profile and the power losses. Figure 2-4 is a single line diagram of IEEE 33 buses system.

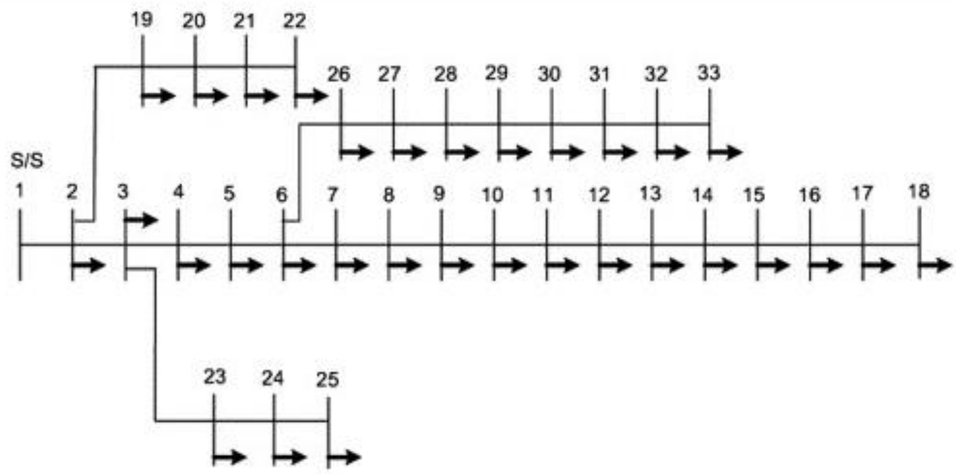

Figure 2-4 (resource: http://pubs.sciepub.com/wjcse/2/1/3/figure/2)

Figure 2-5 shows the voltage profiles for the IEEE 33-bus system if there is no distributed generation and 0.5MW, 2MW, 3MW distributed generation at bus 9.

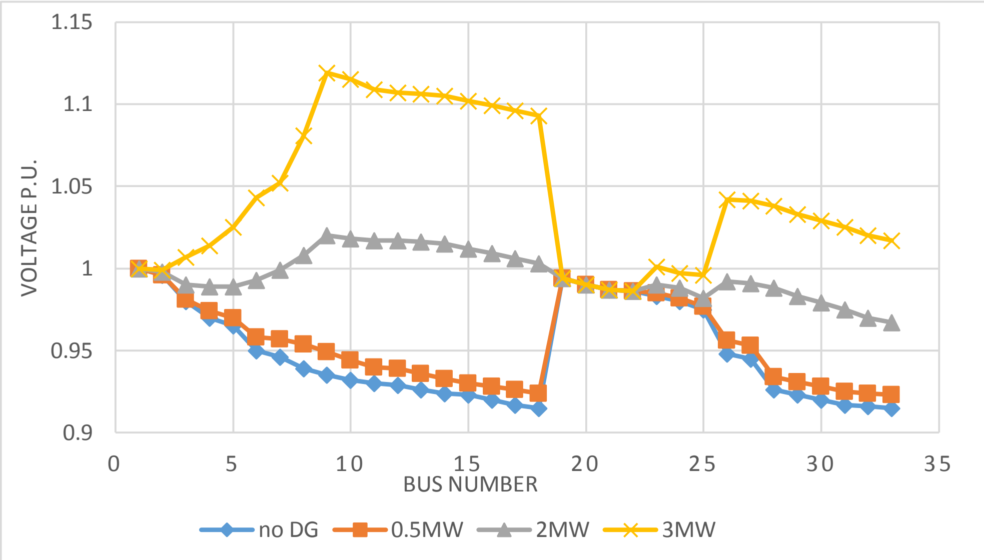

Figure 2-5 Voltage profiles with different DG sizing

From figure 2-5, we can see that the no DG network voltage profile is generally low. If there are different capacities of distributed generation at bus 9, the power flow changes and the bus voltage becomes higher. However, if the capacity of distributed generation is too high, such as 3MW in Figure 2-5, some of the bus voltages would be higher than the acceptable voltage limit and this could lead to many negative impacts such as safety problems. Thus, finding an optimal size of distributed generation is necessary to improve the voltage profiles and make sure the system operates safely as well.

Figure 2-6 shows the effects of changing the DG location, but not capacity of the distributed generation, on the voltage profiles. In this scenario, 0.5MW distributed generation is placed on buses 7, 14 and 16 respectively, and results are compared with no distributed generation system.

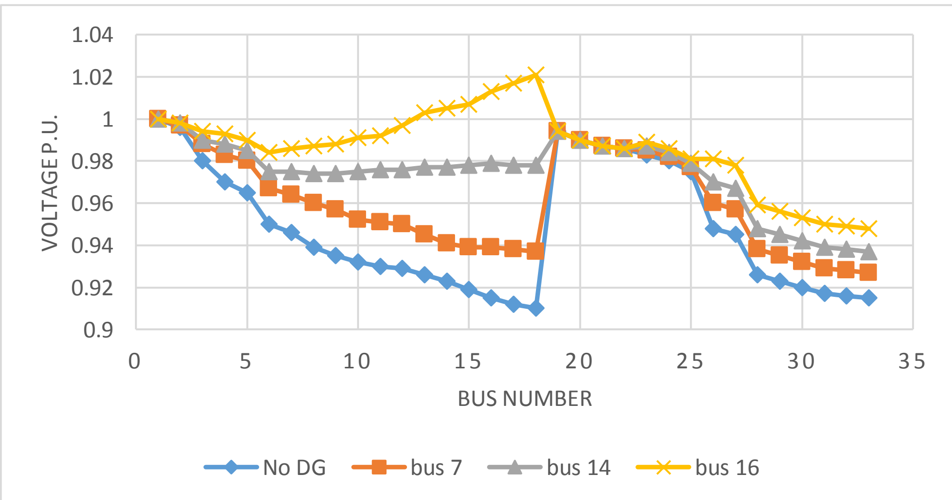

Figure 2-6 Voltage profiles with different bus positions

From figure 2-6, when the capacity of distributed generation remains constant, the location will influence the voltage profile of the network as well. When the distributed generation is closer to the substation (bus 7), the voltage is influenced less, if the distributed generation is on buses 14 or 16 which are closer to the end of line, the effects of distributed generation are more obvious.

Figure 2-7 shows the active power losses when install 0.5MW, 0.7MW, 2MW, 2.6MW, 3MW, 3.6MW and 4MW distributed generation are installed on bus 9.

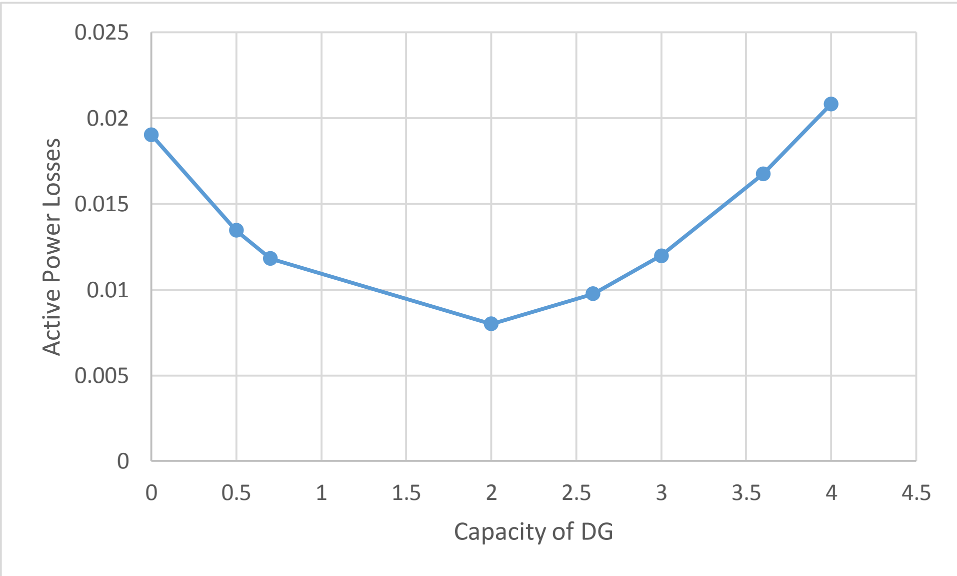

Figure 2-7 Active power losses with different DG sizing

From figure 2-7, if the capacity of distributed generation increase, the active power losses will drop at first but increase after a value. Therefore, finding the optimal allocation of distributed generation will help us to produce less losses. In this case, the optimal generator capacity on bus 9 would be 2MW.

2.5 Conclusion

In this chapter, the definition of distributed generation has been introduced at first, followed by the brief introduction to some types of distributed generation including wind power, solar power, fuel cells and cogeneration. Secondly, summed up the impact of distributed generation on the network, and simulated IEEE 33 buses system to prove that the capacity and location of distributed generation can affect the voltage and the losses of network. Optimal allocation of distributed generation can bring a better performance of distributed network.

Chapter 3 Find the Optimal Allocation of Distributed Generation by Adaptive Genetic Algorithm

3.1 Introduction

Distributed generation can influence the power losses and the voltage levels. In order to plan an optimal sizing and site of distributed generation, this project build a system with a multi objectives including lowest investment cost, lowest power losses and best voltage levels. This project simulated IEEE 14 buses system and finds optimal placement and sizing of distributed generation by using genetic algorithm. In order to have better accuracy and the convergence speed, adaptive genetic algorithm will be used.

3.2 Mathematical Model of Optimal Allocation of Distributed Generation

3.2.1 Objective Function

To build a system with lowest investment cost, lowest power losses and best voltage levels, the objective function can be set by:

$$minF = f(bus, size) = \min\{\bar{C}_{DG} + \bar{C}_{loss}, \bar{V}_M\}$$

(3-1)

Where, $\bar{C}_{DG}$ and $\bar{C}_{loss}$ are the investment cost and power losses cost respectively. $\bar{V}_M$ is the quality of voltage levels.

The variables are the bus numbers and the capacities of distributed generators.

The cost of DG is linearly related to the investment cost, so the cost can be defined as:

$$\bar{C}_{DG} = \sum_{i=1}^{N_{DG}} C_i P_{DGi}$$

(3-2)

Where N_{DG} is the number of buses which are connected with DG, C_i is the unit investment cost of installed distributed generation, P_{DGi} is the rated power of distributed generation which is attached to bus i.

Due to DG access to the network, the active power loss of the network will be changed. The active power losses can be indicated by the losses cost. The lowest losses cost means the lowest power losses, so $\bar{C}_{loss}$ is the objective function of the power losses [14].

$$\bar{C}_{loss} = \sum_{i=1}^{L} C_e t_{imax} R_i \frac{P_i^2}{(U_N \mu_i)^2}$$

(3-3)

Where, L is the number of branches, $C_e$is the unit price of electricity, t_{imax} is the max working time of the load, $R_i$is the resistance of branch i, $U_N$is the rated voltage, $\mu_i$is the power factor of load i. P_i is the power of the load on bus i

Due to DG access to the network, the voltage quality will be changed. The objective function of voltage levels quality is shown as:

$$\bar{V}_M = \sum_{i=1}^{N} (U_i - U_{ideal})^2$$

(3-4)

Where, N is the number of buses, U_{ideal} is the ideal steady voltage

The objective function is a multi-objective function, so there should be a balance coefficient μ, the balance is indicated to the importance of each consideration. The final objective function is defined by:

$$f(bus, size) = \min\{\mu(\bar{C}_{DG} + \bar{C}_{loss}) + (1-\mu)\,\bar{V}_M\}$$

(3-5)

3.3 Constraints

3.3.1 Equality constraints

Power balance at each node - power flow equations [30]

$$\begin{cases} P_{Gi} - P_{loadi} - U_i \sum_{k=1}^{N} U_k \,(G_{ki}\cos\theta_{ki} + B_{ki}\sin\theta_{ki}) \\ Q_{Gi} - Q_{loadi} - U_i \sum_{k=1}^{N} U_k \,(G_{ki}\cos\theta_{ki} - B_{ki}\sin\theta_{ki}) \end{cases} \qquad k = 1, \ldots . N$$

(3-6)

Where, P_{Gi}, Q_{Gi} are active and reactive power on node i. P_{loadi}, Q_{loadi} are active and reactive power of the loads on node i. U_i, U_k are voltages on node i and k respectively. G_{ki}, B_{ki}, θ_{ki} are the conductivity, susceptance and the phase angle between nodes i and k.

3.3.2 Inequality constraints

A. Voltage of the bus

The voltage range should be in a range according to the local standard. So the bus voltage should be in the required range.

$$U_{imin} \leq U_i \leq U_{imax} \qquad i = 1,2,3, \dots, N \tag{3-7}$$

B. The power on transmission lines

$$P_{imin} \leq P_i \leq P_{imax} \qquad i = 1,2,3, \dots, N \tag{3-8}$$

C. The power of DG

$$0 \leq P_{DGi} \leq P_{DGimax} \qquad i = 1,2,3, \dots, N_{DG} \tag{3-9}$$

D. The constraint on sum of powers of all distributed generation which is access to the distributed network

Some of the output power of distributed generation is not stable. The output power may be affected by location or weather, such as wind and PV generation. There will be some negative influence on network because of the high power of DG, such as voltage fluctuations, so the total power of DG should be constrained [31].

$$\sum S_{DG} \leq \gamma \sum S_{load} \tag{3-10}$$

Where, $\sum S_{DG}$ is the total power of accessed DG to the network. $\sum S_{load}$ is the total power of load in network. γ is the maximum ratio of accessed DG sizing to the total power of loads in the network.

3.4 Adaptive Genetic Algorithm

3.4.1 Introduction of Genetic Algorithm

Genetic Algorithm (GA) is an artificial intelligence random search algorithm which is researched and optimized based on a natural genetic rule [32]. The genetic algorithm was invented by John Holland in the 1960s and became popular through his book Adaptation in Natural and Artificial Systems in 1975 [33]. The genetic algorithm is an efficient, parallel, global optimization method. It uses the principle of survival of the fittest to find an approximate optimal solution in the potential solutions. In every generation of the genetic algorithm, the fitness of each individual is used to select the most fit individuals and let them generate more fit individuals, just like evolution in nature. The genetic algorithm proposed by John Holland is the Simple Genetic Algorithm (SGA) [34]. The Simple Genetic Algorithm is easy to understand and simple to operate. It is the basis of all subsequent genetic algorithms. The most common improved genetic algorithms include Hierarchic Genetic Algorithm, Messy Genetic Algorithm, Adaptive Genetic Algorithm, Niched Genetic Algorithm and Parallel Genetic Algorithm [35]. The main advantage of Genetic Algorithms is that no matter what the problem is, the genetic algorithm follows the same simple process: encoding, selection, crossover and mutation. With the development of research on the genetic algorithm, it is already being used on optimization problems in many fields, such as engineering science, computer-automated design, management sciences and social sciences [36].

The important features of the genetic algorithm: (1) Genetic Algorithms can be used in a lot of fields, no matter what the problem is, the same algorithm can be used. (2) They are highly adaptive, operate searching by using the optimization information, inherited the good gene chromosome to the next generation and eliminate the bad chromosome. (3) They are scalable, they are easy to combine with other algorithms such as Simulated Annealing Algorithm and Conjugate Gradient [37]. (4)They are easy to understand, as the theory is similar to biological inheritance.

3.4.2 The Components and Methodology of Genetic Algorithm

A. Coding

Coding converts abstract variables into coded form. In the genetic algorithm, coding converts the variables into a code string with specified symbols and in certain order, just like the gene on a chromosome in natural genetics. Each string can stand for a chromosome or an individual. Due to the wide application, field of genetic algorithm, there are several ways to encode variables such as binary encoding, floating point encoding, symbol coding and integer coding. The most common coding is binary coding which is a string with just digits 0 and 1. This code is simple and easy to operate but it cannot show the features of an individual directly. This project will use integer coding, which means converting the variable into integer number strings as the chromosomes. Integer codes can shorten the length of strings and save the time of decoding.

B. Creating the initial population

A simple genetic algorithm creates many chromosomes randomly under the constraint conditions. The number of chromosomes is the population size. Enlarging the population size can increase the search scope, leading to more accurate solutions, but it is not always necessary to have a so large population. So the researchers should find a suitable size of population. This initial population is a set of many possible solutions. The genetic algorithm will start from this generation, and select and inherit the high fitness individuals for the next generation. Genetic algorithm simulate natural evolution with the principle of survival of the fittest, and eventually get the optimal individual to satisfy the problem requirement.

C. Fitness

Fitness is a value which is measuring the quality level of each individual. The value of fitness can influence the probability of being selected for the next generation. The fitness value is calculated using a function that is related to the objective function, and the value must be a non-negative number. High fitness value means high quality of the individual. The fitness function can affect the convergence speed of genetic algorithm.

Some common ways to calculate the fitness value [38]:

a. Convert the objective function into fitness function directly

$$\mathrm{Fit}(\mathrm{f(x)}) = \begin{cases} f(x) & maximization\ problem \\ -f(x) & minimization\ problem \end{cases}$$

(3-11)

where $f(x)$ is the objective function.

This function is simple and intuitive, but the fitness value may be negative. This method is suitable for some simple problems.

b. Limits estimation.

For minimization problems:

$$\mathrm{Fitness}(\mathrm{f(x)}) = \begin{cases} C_{max} - f(x), & f(x) < C_{max} \\ 0, & f(x) \geq C_{max} \end{cases}$$

(3-12)

For maximization problems:

$$\text{Fitness}(\text{f(x)}) = \begin{cases} f(x) - C_{min}, & f(x) > C_{min} \\ 0, & f(x) \le C_{min} \end{cases}$$

(3-13)

where, C_{max} is the maximum value that is estimated for the objective function, C_{min} is the minimum value that is estimated for the objective function. However, the limits may not be estimated accurately.

c. Reciprocal function

For minimization problems:

$$\text{Fitness}(\text{f(x)}) = \frac{1}{1 + c + f(x)} \qquad c \ge 0, c + f(x) \ge 0$$

(3-14)

For maximization problems:

$$\text{Fitness}(\text{f(x)}) = \frac{1}{1 + c - f(x)} \qquad c \ge 0, c - f(x) \ge 0$$

(3-15)

where, c is a number that ensure that $c + f(x)$ and $c - f(x)$ are non-negative. This method is used in this project to define the fitness value.

D. Selection

Selection in genetic algorithms is selecting individuals with high fitness and grouping these individuals into a new population according to the fitness value to keep the better individuals for the next generation, thereby making the individuals in the population come close to the optimal solution gradually. The common methods of selection include: truncation selection, tournament selection, stochastic universal sampling and roulette wheel selection [39]. Roulette wheel selection is used in this project.

Roulette wheel selection (also called fitness proportionate selection) means the probability of being selected as an individual depends on the proportion of its fitness in the sum of all individual fitness values. High proportion means high probability of being selected. The probability is given by the function:

$$P_i = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)} \qquad i = 1,2, \dots N$$

(3-19)

where, $f(x_i)$ is the fitness value of the individual and N is the population size.

E. Crossover

Crossover is a genetic operator to change the programming of chromosomes from the parent generation to the next generation with a certain probability. Crossover is exchanging a part of two or more chromosomes randomly to produce a new individual. We expect crossover can combine the good genes together in order to produce a better solution and get closer to the optimal solution. It is like the reproduction and biological crossover based genetic algorithm [40]. There are many crossover techniques depending on different data structures. The most common technique is one-point crossover, which is used in this project. One-point crossover means choosing one crossover point on both parents' chromosome strings and swap the data beyond that point between the two parents' chromosomes. The resulting strings are the children.

For example, two seven digits binary strings as parents, 1011101 and 1110010. If the crossover occurs from the 4th digit, then this lead to children as shown below.

Parents	A: 101	1101
	B: 111	0010
		Crossover point
Children	A: 101	0010
	B: 111	1101

F. Mutation

Mutation is changing one or more genes on a chromosome string thereby producing a new individual with a low probability. Mutation in genetic algorithms is a genetic operator which can avoid losing some genes during the selection and crossover steps, avoid the prematurity, maintain genetic diversity and increase the accuracy of genetic algorithm. Prematurity means in the early period of genetic algorithm, there is an individual fitness much higher than the average fitness in the population, which leads to high probability of selection, genetic diversity will drop rapidly and the result will be suboptimal. Crossover and mutation are the main operator and the secondary operator for producing new individuals. Decent crossover and mutation can enlarge the area of global and local search. An example of mutation is given below:

Individual A: 1001011, assume mutation on the 5th digit

A:	1001011

Mutation: 1001111

G. Crossover and mutation probabilities

Crossover probability is the ratio of how many couples of chromosomes will be picked to cross in the population. For example, if the population size is 100, then there are 50 couples of chromosomes. If the crossover probability is 0.8, then 40 couples will cross over.

Mutation probability is the ratio of random elements of the chromosome that will be changed into something else. For example, if this is a binary string with 50 digits in length and has a 2% mutation probability, then it means that 1 of the 50 bits will be picked up at random and will mutate.

H. Find the best solution in every population

A new generation is produced by selection, crossover and mutation. The best individual should be found and recorded to avoid losing the best solution during crossover and mutation. If the best individual reaches a terminating condition, the calculation will be finished.

I. Termination

The generational process from selection to mutation will be repeated until a terminating condition has been reached [41]. Some common termination conditions are:

a. A satisfactory solution has been found.

b. A fixed number of iteration has been reached.

c. A budget has been reached, such as time or money.

d. The highest fitness solution is not changing which means there is no longer a better solution being produced in successive iterations.

e. Manually inspecting the rate of convergence.

f. Combinations of the above

The process of simple genetic algorithm can be shown in a flow chart below.

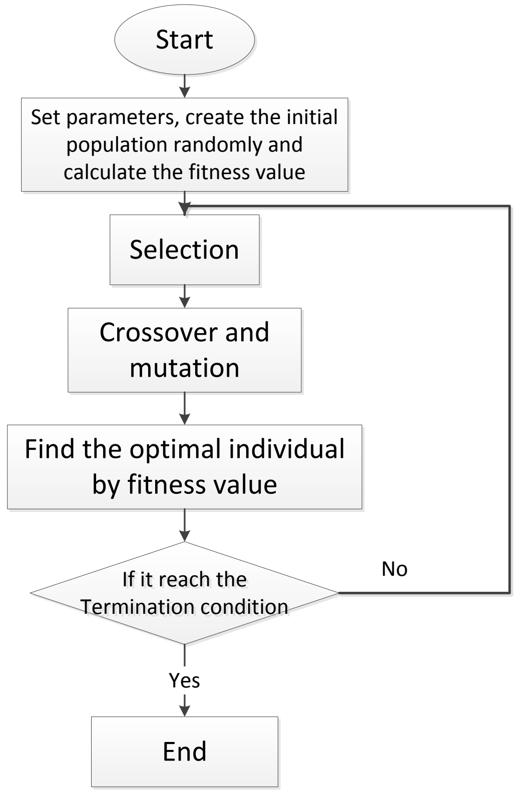

Figure 3-1 Flow chart of Simple genetic algorithm

3.4.3 Adaptive Genetic Algorithm

Adaptive genetic algorithm is an improved algorithm based on the simple genetic algorithm. In the simple genetic algorithm, the probabilities of crossover (P_c) and mutation (P_m) are fixed values, generally be chosen from the range [0, 1]. In adaptive genetic algorithms, the probabilities of crossover and mutation will be adjusted depending on the fitness of each individual. The probabilities of crossover and mutation can influence the level of solution accuracy and the convergence speed [42]. The probabilities of crossover and mutation are defined as functions (3-20):

$$P_c = \begin{cases} \dfrac{k_1(f_{max} - f')}{f_{max} - f_{avg}}, & f' \geq f_{avg} \\ k_2, & f' < f_{avg} \end{cases}$$

$$P_m = \begin{cases} \dfrac{k_3(f_{max} - f)}{f_{max} - f_{avg}}, & f \geq f_{avg} \\ k_4, & f < f_{avg} \end{cases}$$

(3-20)

Where, P_c is the probability of crossover, P_m is the mutation probability, f_{max} is the maximum value of fitness of individual in the population, f' is the higher ranking fitness value of the two individuals to be crossed, f_{avg} is the average fitness value of the population, f is the fitness of the individual,

k_1, k_2, k_3 and k_4 are chosen in[0,1.0]. k_3 is the default crossover probability, generally chosen in [0.8, 0.99]. k_4 is the default mutation probability generally chosen in [0, 0.5].

From equation (3-20), we can see if the individual fitness is higher than the average fitness. If the fitness value is higher, its crossover and mutation probabilities will be lower and at the highest fitness solutions crossover and the mutation probabilities will be 0. Otherwise, if the fitness is lower than the average fitness value, the individuals' crossover and mutation probabilities will be fixed. So in the adaptive genetic algorithm, if an individual fitness value is high, it will have a lower probability to cross and mutate, which means it is "protected" [43]. If an individual fitness value is lower, it will have a higher probability to cross and mutate to produce new individuals and be eliminated. However, there is an obvious shortcoming to the adaptive genetic algorithm. In the early stages of the algorithm, if the best individuals remain unchanged, we cannot ensure the present best solution is the global optimal solution, and this situation may give a suboptimal solution [43].

Therefore, the adaptive mutation probability is used in this project only. In order to maintain genetic diversity and high probability of good gene combination, the good solution will not be protect in crossover aspect.

3.4.4 The Method and Procedure of Using Adaptive Genetic Algorithm to Solve Optimal Distributed Generation Allocation Problem

Import the data of system. The chromosomes would be shown by $X = \{x_1, x_2, \dots x_i \dots, x_n\}$, x_i means the placement and sizing of DG on node i. $x_i = 0$ means no DG on bus i. $x_3 = 1$ means the sizing of DG on bus 3, $P_{DG3} = 100kW$. $x_3 = 2$ means the sizing of DG on bus 3, $P_{DG3} = 200kW$.

Run the system and calculate all individual objective functions and fitness values. According to the fitness value, select numbers of best individuals to group as a parent population. Operate crossover and mutation on the individuals of the parent population. Get the new individuals under selection and make a new generation with these as parents. Keep recording the best individuals in every generation during the entire calculation.

Repeat operation until the termination condition has been reached which is reaching 30 iterations.

The flow chart is as shown below:

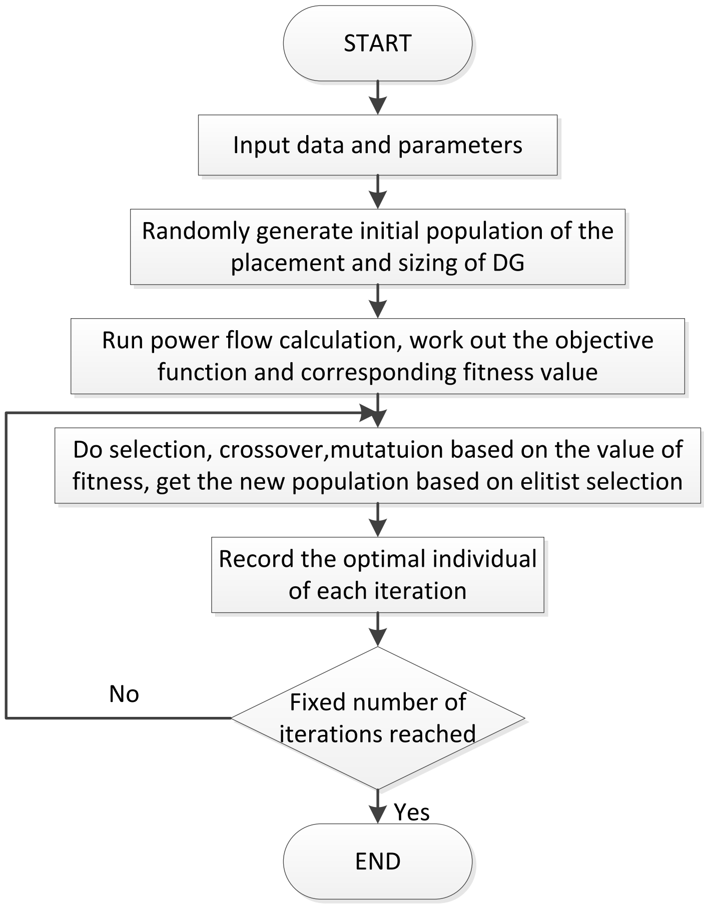

Figure 3-2 Flow chart of genetic algorithm

3.5 Case Study

The objective function is made up of investment cost, power losses cost and voltage profiles quality, and the methods are tested on the IEEE 14-bus system using Powerfactory.

Figure 3-1 is the single line diagram of IEEE 14-bus system

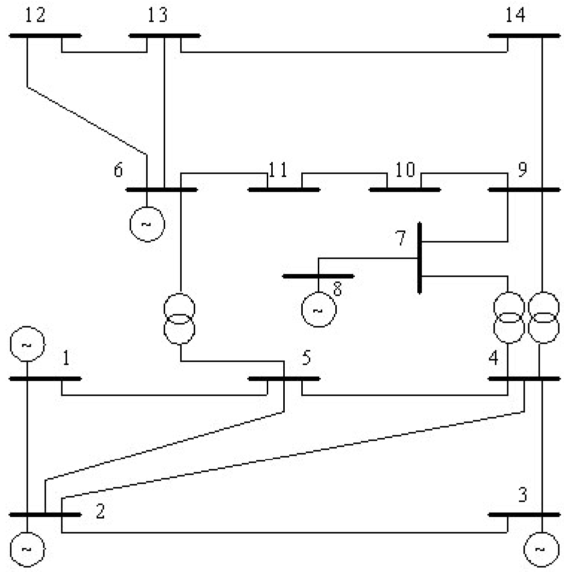

Figure 3-3 IEEE 14-bus system SLD (resource: http://al-roomi.org/power-flow/14-bus-system)

Total capacity of distributed generation is constrained to 30% of the total load. Each capacity of distributed generation is constrained in 100kW to 900kW. Four distributed generators are planned to be installed in the distributed network. The distributed generators can only be installed on buses 4, 5, 7, 9, 10, 11, 12, 13, and 14 because there are already generators on buses 1, 2, 3, 6 and 8.

The chromosome codes are defined as $\{x_1\ x_2 \ldots x_9\}$. For example, 060500702 means distributed generation capacities are 600kW, 500kW, 700kW, 200kW and be installed on buses 5, 9, 12, 14 respectively. The investment cost is assumed as \$1300/kW [14]. Unit price of electricity is \$0.2 per kWh [44]. Max operating time of the load $\tau = 3000\text{h}$.

<u>Parameters of Genetic algorithm:</u>

Initial population size is 30, Maximum iterations is 30.

Crossover probability. $P_c = 0.9$.

Mutation probability

$$P_m = \begin{cases} \dfrac{k_3(f_{max} - f)}{f_{max} - f_{avg}}, f \geq f_{avg} \\ k_4, \qquad\qquad f < f_{avg} \end{cases}$$

$$k_4 = k_3 = 0.2$$

(3-21)

The objective function:

$$f(bus, size) = \min\{\mu(\bar{C}_{DG} + \bar{C}_{loss}) + (1 - \mu)\,\bar{V}_M\}$$

(3-22)

The balance coefficient $\mu = 0.5$

Ideal stable voltage $U_{ideal} = 1.06\ p.u.$

Results:

Table 3-1 shows the optimal results of the allocation of 4 distributed generators in the IEEE 14-bus system by using adaptive genetic algorithm. Installing 200kW, 500kW, 500kW and 300kW distributed generation on bus 4, 9, 12 and 13 respectively is the optimal solution in this project.

Table 3-1 optimal solution with adaptive genetic algorithm

Bus Number	Capacity/kW	Investment Cost	Losses Cost
4	200	$1,950,000	$4,920,000
9	500		
12	500		
13	300		

Table 3-2 Power losses comparison

Power losses with no distributed generation	Power losses with the optimal distributed generation with adaptive genetic algorithm	Reduction in Power	Reduction Ratio
9.287MW	8.200MW	1.087MW	11.71%

Table 3-2 shows the degree of the reduced active power losses. From the results, the original active power losses mean that no distributed generation was installed 9.287MW. After connecting the distributed generation to the network, the active power losses are reduced to 8.2MW. The reduced active power losses are approximately 11.71% of the initial power losses in the network.

Figure 3-4 shows the voltage levels changes before and after installing distributed generation. It is obvious that the voltages are more stable than the system with no distributed generation. From Table 3-3, the voltage quality is 0.059 p.u. and the voltage after installing distributed generation is 0.016 p.u. so the voltage quality has been improved.

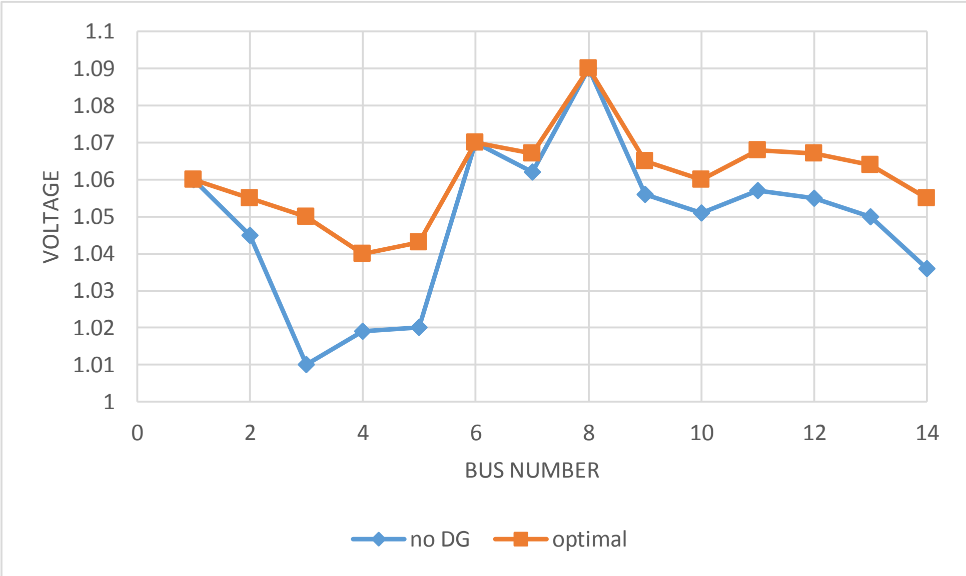

Figure 3-4 The Voltage comparison between no DG and optimized network

Voltage levels quality in p.u. with no distributed generation $\bar{V}_M = \sum_{i=1}^{N} (U_i - U_{ideal})^2$	The optimal distributed generation voltage levels quality in p.u. with adaptive genetic algorithm
0.059	0.016

Table 3-3 voltage levels quality comparison

Figure 3-5 shows the best objective function value in every iteration. The best objective function value was reduced with the iteration, that is, the adaptive genetic algorithm was optimizing the solution since this project is doing a minimization problem. The adaptive genetic algorithm converged at the 24th iteration for this project. So, adaptive genetic algorithm is an effective algorithm to find the optimal solution for the objectives what were expected.

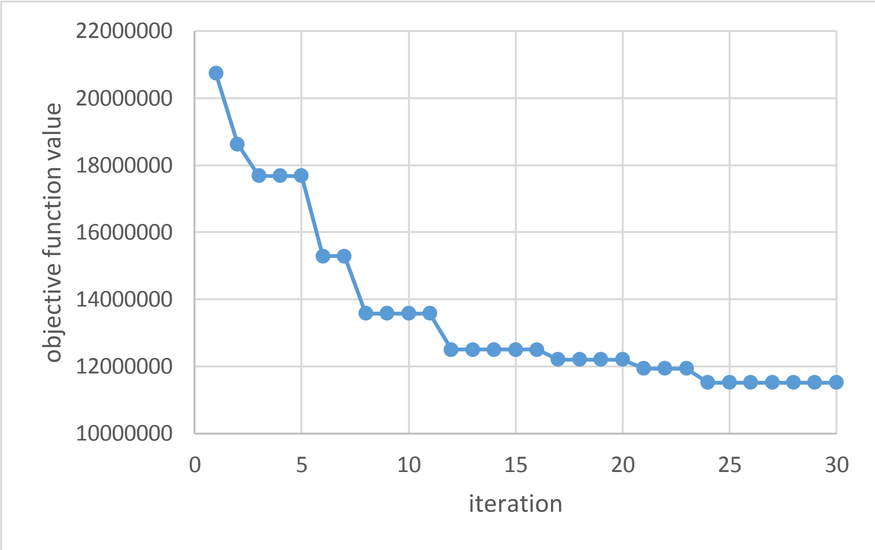

Figure 3-5 Adaptive Genetic Algorithm Convergence process

From the results presented above, installing distributed generation can improve the performance of distributed network system and adaptive genetic algorithm is an effective method to find the optimal placement and capacity of distributed generation.

Chapter 4 Future Research

To plan an optimal allocation of distributed generation in a distributed network, the power losses and the voltages are not the only two variables that should be considered. They are just the variables that can be expected for most of general problems of optimal allocation of distributed generation. In practical applications, there are some other factors that can influence the results:

1. The types of distributed generation [45]. Different types of distributed generation will have different performances of power supply. Some types of distributed generation are influenced by the location, weather, seasons and environment. For example, the performances of wind generation and PV generation are impacted by the weather conditions and the locality. The output power of wind generation depends on the wind speed of that location. The output power of PV generation will be influenced by sun light intensity of the placement. In addition, not all of types of distributed generation can be installed in anyplace, some placements are not fit with PV power or hydro power. So in practical applications, the planner should also consider about place the optimal types of distributed generation on decent placements.

2. The total cost of installing distributed generation is not just the investment cost and the power losses cost [46]. In practical applications, there will be some consecutive costs during the system operation, such as the pollution penalty cost and the cost of power shut down (caused by malfunction or damage). The pollution penalty cost depends on the power generation of the buses. The power shut down cost depends on the customer loads of the buses. They are all related to the sizing and the site of the distributed generation. Therefore, considering some consecutive costs might be more accurate for the planning.

3. There are a lot of researchers and departments researching about the optimal allocation of distributed generation in distributed networks. So not only the genetic algorithm can solve this problem, but also some other excellent ideal or algorithms can find out the optimal solution, such as the Nonlinear Optimization Algorithm and the Particle Swarm Optimization algorithm. In addition, genetic algorithm has scalability, in that it can combine with some other algorithms. Some other methods to solve this problem are mentioned in the background part of this report. In the future work, make comparison with some other algorithms to find the best algorithm to solve this problem.

Conclusion

With the development of power generation and the growth of electricity demand of the costumers, it is important to make the distributed network be more reliable and economical. Generally, installing distributed generation with decent placement and capacity in the distributed network can improve the voltage levels and reduce the power losses to make the distributed network operate reliably and economically. This report has researched about finding an algorithm to optimize the capacity and the site of distributed generation in distributed network, based on readings and research on many literature around the world. The report has theoretical analysis and simulation results on the problem and the results are

1. Analyze how the distributed generation will affect the distributed network at first from several of literatures. The results are the voltage profiles and power losses will be changed by distributed generation and use two simple models to present the theoretical derivation. What is more the capacity of distributed generation, the voltage levels will be improved, however if the capacity is too high, it will lead to power backflow and the voltage levels may exceed the safe demand voltage range. In addition, the voltage will be higher if the distributed generation is located closer to the end of a feeder line. Decent allocation of distributed generation will also improve the power losses of the system, too high capacity of distributed generation may increase the power losses. In order to prove the derivation, IEEE 33-bus system was simulated and the results are closed to the derivation.

2. To build a lowest investment and power losses cost and the most stable voltage profile, the adaptive genetic algorithm was used to optimize the allocation of distributed generation in a distributed network. Genetic algorithm is a simple and easy to understand optimization algorithm. In the mathematical model of the problem, the objective function consists investment cost, power losses cost and the voltage levels quality. Simulating IEEE 14 bus system was used as a case study. The results present the optimal solution can obviously make the voltage profiles be more stable and reduce about 12% of power losses. Genetic algorithm is an efficacious algorithm to find the optimal sizing and the site of distributed generation in a distributed network.

3. For the future research, considering about the types and consecutive costs is better for the practical application. In addition, some other optimization algorithms can also solve this problem. Genetic algorithm can be compared with the other algorithms to find the best way to access the optimal allocation of distributed generation to distributed networks.

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Appendix

Appendix A Data Sheet of IEEE 33 Buses System [47]

Branch Number	Sending Bus-Receiving Bus	Resistance Ω	Reactance Ω	Nominal Load at Receiving Bus	
				P(KW)	Q(KW)
1	1-2	0.0922	0.047	100	60
2	2-3	0.493	0.2511	90	40
3	3-4	0.366	0.1864	120	80
4	4-5	0.3811	0.1941	60	30
5	5-6	0.819	0.707	60	20
6	6-7	0.1872	0.6188	200	100
7	7-8	0.7114	0.2351	200	100
8	8-9	1.03	0.74	60	20
9	9-10	1.044	0.74	60	20
10	10-11	0.1966	0.065	45	30
11	11-12	0.3744	0.1298	60	35
12	12-13	1.468	1.155	60	35
13	13-14	0.5416	0.7129	120	80
14	14-15	0.591	0.526	60	10
15	15-16	0.7463	0.545	60	20
16	16-17	1.289	1.721	60	20
17	17-18	0.732	0.574	90	40
18	2-19	0.164	0.1565	90	40
19	19-20	1.5042	1.3554	90	40
20	20-21	0.4095	0.4784	90	40
21	21-22	0.7089	0.9373	90	40
22	3-23	0.4512	0.3083	90	50
23	23-24	0.898	0.7091	420	200
24	24-25	0.896	0.7011	420	200
25	6-26	0.203	0.1034	60	25
26	26-27	0.2842	0.1447	60	25
27	27-28	1.059	0.9337	60	20
28	28-29	0.8042	0.7006	120	70
29	29-30	0.5075	0.2585	200	600
30	30-31	0.9744	0.963	150	70
31	31-32	0.3105	0.3619	210	100
32	32-33	0.341	0.5302	60	40

Appendix B Data sheet of IEEE 14 buses system [48]

Branch Number	Sending Bus-Receiving Bus	Resistance Ω	Reactance Ω	Bus Number	Nominal Load at the Bus	
					P	Q
1	1-2	0.01938	0.05917	2	21.7	12.7
2	2-3	0.04699	0.01979	3	94.2	19
3	2-4	0.05811	0.17632	4	47.8	-3.9
4	1-5	0.05403	0.22304	5	7.6	1.6
5	2-5	0.05695	0.17388	6	11.2	7.5
6	3-4	0.06701	0.17103	9	29.5	16.6
7	4-5	0.01335	0.04211	10	9	5.8
8	7-8	0	0.17615	11	3.5	1.8
9	7-9	0	0.11001	12	6.1	1.6
10	9-10	0.03181	0.0845	13	13.5	5.8
11	6-11	0.09498	0.1989	14	14.9	5
12	6-12	0.12291	0.15581			
13	6-13	0.06615	0.13027	Bus Number	Generator Output Power	
14	9-14	0.12711	0.27038			
15	10-11	0.08205	0.19207		P(MW)	Q(MW)
16	12-13	0.22092	0.19988	1	232.38	-16.89
17	13-14	0.17093	0.34802	2	40	42.4
18	5-6	0	0.25202	3		23.39
19	4-7	0	0.20912	6		12.24
20	4-9	0	0.55618	8		17.36